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Published

2020

Journal Title

Vietnam Journal of Computer Science

Version

Version of Record (VoR)

DOI

10.1142/S219688882050013X

Vietnam Journal of Computer Science
Vol. 7, No. 3 (2020) 231–250

DOI: 10.1142/S219688882050013X

Designing Personalized Learning Environments — The Role of Learning Analytics

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Received 8 December 2019
Accepted 25 February 2020
Published 20 March 2020

Learning analytics, as a rapidly evolving field, offers an encouraging approach with the aim of understanding, optimizing and enhancing learning process. Learners have the capabilities to interact with the learning analytics system through adequate user interface. Such systems enables various features such as learning recommendations, visualizations, reminders, rating and self-assessments possibilities. This paper proposes a framework for learning analytics aimed to improve personalized learning environments, encouraging the learner's skills to monitor, adapt, and improve their own learning. It is an attempt to articulate the characterizing properties that reveals the association between learning analytics and personalized learning environment. In order to verify data analysis approaches and to determine the validity and accuracy of a learning analytics, and its corresponding to learning profiles, a case study was performed. The findings indicate that educational data for learning analytics are context specific and variables carry different meanings and can have different implications on learning success prediction.

Keywords: Learning analytics; personalized learning environment; education; framework.

1. Introduction

Recently, educational data analysis, such as learning analytics (LA), academic analytics (AA) and educational data mining (EDM), has been established as an innovative research area.[1] LA, which has been applied to real-time modeling, utilizes dynamic and static information about learning process, learning environments, personal information about learners, optimization of learning processes, and educational decision making.[2,3] AA refers to the significant patterns discovery in

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educational data, proposes practical strategies and reports academic issues (e.g. maintenance, progress rates).[4] The procedure of mining valuable data out of a large collection of complex educational datasets is known as EDM.[5] The shared aims of all these concepts (LA, AA, EDM) have relevance to educational data processing. Only the LA concept gives special importance to the optimization of learning environments and learning processes in real time. Personalized learning encourages the active involvement of learners in the learning process by improving learning experiences and outcomes, it consists of the following processes [6]:

- Understanding the needs and interests of learners.
- Preparing teaching material, appropriate syllabuses and resources that encourage more comprehensive learning.
- Providing relevant learning experiences that meet the unique learning profile of each learner.

Educators use LA to attain insights and adjust the learning processes. Principally, LA refers to the application of analytic techniques to effectively analyze and use of educational datasets, which includes providing data about learner and teacher activities and identifying behavior patterns in order to support the learning process.[7] Many researchers and developers studied the use of LA in different fields related to the data availability, the competence, the cost, the privacy, the relevance and the ownership.[6–8] In this paper, we propose design and implementation of a framework for integration of heterogeneous LA techniques providing personalized recommendations for suitable learning resources, learning paths, or peer learners through recommending system. In order to verify data analysis, and to determine the validity and accuracy of a LA process and its correspondence to learning profiles, we have performed a case study. The findings indicate that educational data for LA is context specific and variables carry different meanings and can have different implications on learning success prediction.

The rest of the paper is organized as follows. Section 2 gives an overview of key trends in education environments, dataset and LA. Section 3 is devoted to educational LA applications, features and their role in personalized learning environments (PLEs). In order to identify predictive models for learner success logistic regression tests were performed and pointed out in Sec. 4. Experimental case studies for validating learner profiles, obtained by applying LA, are presented. The general discussion critically reflects on the results, suggests implications and addresses concerns of LA. Section 5 of the paper provides the concluding remarks and possible future research.

2. Background

Recently, a lot of higher education institutions have been developing and implementing their own LA systems to support higher quality learners' learning activities.[9] Learners interact through the adequate user interface of the LA system, which offers different features of highly adaptable and PLE. PLEs can help to encourage learner's skills to manage, monitor, as well as reflect their own learning.[10] To be able to design, develop, and implement personalized LA systems, it is necessary that the educational institutions comprehensively investigate what learners expect from these systems. LA aims to combine historical and current user data to provide useful information during learning activities.[11] Several frameworks have been proposed concerning these issues.[12,13] d'Aquin *et al.* argue for a closer relationship between LA and linked data with emphasis on semantic web technologies.[14] However, this approach does not include valuable information of learner's background knowledge and skills as well as variety of curricular requirements. Some frameworks concentrate on Social Learning Analytics (SLA) in which learners' discussion activities are visualized using data mining and visualization tools.[15,16]

Widely available and used in educational systems are visualization tools, such as Moodle dashboard,[17] which tries to make an analysis of some interactions in a course through visualizations. CAMERA, another tool used for monitoring and reporting on learner actions, also can foster learning process reflection in PLEs. This tool has the ability to track and collect usage of metadata from various application programs in the form of Contextualized Attention Metadata (CAM) and generates report on learning behavior.[18] While GLASS, as a Web-based visualization platform, is able to connect to more than one different CAM databases, thus allowing access to recorded events gained in diverse learning actions. The architecture of the tool has been developed to provide an adaptable, modular platform that supports a great number of new modular visualizations.[19] Tools integrated in the online WebCT platform, such as CourseVis, use different information visualization techniques for graphically rendering multidimensional and complex learner data, therefore simplifying the implementation of new visualizations.[20]

There are also several other LA tools that provide teachers and educators with feedback on learners' learning activities and progress.[21] LOCO-Analyst, as an example of LA tool, generates variety of feedback based on the analysis of learner tracking data: (1) all kinds of learner activities performed during the learning processes; (2) the usage of the learning material educators had deployed in the LMS and (3) social interactions between learners in different virtual learning environments.[22] Predicting learners' learning success and providing practical feedback have been two of the most frequently implemented tasks associated with LA.[23] For example, the Khan Academy platform already provides powerful LA visualizations (e.g. for knowing the learners' progress in different skills or the learners' last activity in the different resources). In addition one example of the new analysis of learning processes, provided by ALAS-KA, presents the analysis and visualizations of effective states.[24] ALAS-KA embraces new types of visualization for individual learners and for the entire class. Based on all the indicators available, individual visualizations can be useful for inspecting the learning styles of learners, though group visualizations can help teachers and learners to make a decision in the learning process. CALM System is an example of a dashboard that was developed on top of an intelligent

Table 1. A comparative analysis of educational LA applications.

Educational LA applications	Key features										Intended goals and role in PLE
	Tracked data				Users		Usability evaluation				
	Artifacts produced	Time spent	Social interaction	Resource use	Teachers	Students	Usefulness	Usability	Effectiveness	Efficiency	
SAM	✓	✓	—	✓	✓	✓	—	✓	—	—	Student's self-reflection and awareness of what and how they are doing
GLASS	✓	✓	—	✓	✓	✓	—	—	—	—	A visualization of learning performance with a comparison whole glass group
SLICE	✓	—	✓	—	✓	✓	—	—	—	—	Support reflection and group discussion
StepUp!	✓	✓	✓	✓	✓	✓	—	✓	—	—	To promote reflection and awareness of their activity
Classroom Salon	✓	—	✓	—	✓	✓	—	—	—	—	To visualize how much each learner contributed and percentage of responses
Student Inspector	✓	✓	—	✓	✓	✓	✓	—	—	—	To keep track of learners' interaction in e-learning systems
Course Signals	—	✓	—	—	—	✓	✓	✓	✓	—	To improve retention and performance outcomes
CALM System	—	✓	—	—	—	✓	—	—	✓	—	Provides self-assessment ratings for topics
Narcissus	—	—	✓	✓	—	✓	—	✓	—	—	To help students see how well they are contributing to the group; improve group-work
Student Success System	—	✓	✓	—	—	✓	—	—	—	—	To identify and treat at-risk students
Course Vis	✓	—	✓	✓	✓	✓	✓	—	✓	✓	To support teacher with more information than available in a standard interface
Moodle dashboard	✓	✓	✓	✓	✓	—	—	—	—	—	Visualize time spent so that teachers can identify potential students at risk

Table 1. (*Continued*)

Educational LA applications	Key features										Intended goals and role in PLE
	Tracked data				Users		Usability evaluation				
	Artifacts produced	Time spent	Social interaction	Resource use	Teachers	Students	Usefulness	Usability	Effectiveness	Efficiency	
LOCO-Analyst	✓	✓	✓	✓	✓	—	✓	✓	—	—	To provide feedback on students' learning activities and performance
Teacher ADVisor	—	—	✓	✓	✓	—	✓	✓	✓	—	To propagate automatically generated advice to a learner
Classroom view	—	✓	—	—	✓	—	—	—	—	—	To support awareness for teachers, the dashboard visualizes collaboration and current activity in online group work
Class-on	✓	✓	—	—	✓	—	—	—	—	✓	To provide feedback to a teacher on whom to help next during lab sessions
OLI dashboard	✓	✓	—	✓	✓	—	✓	✓	—	—	To gain an indication of perceived usefulness for improving learning and teaching
CAMERA	✓	✓	—	✓	—	✓	✓	✓	—	—	To track and collect usage metadata from various application programs, stores them and makes report on learning behaviour
ALAS-KA	✓	✓	—	✓	✓	✓	✓	✓	✓	✓	Enables instructors to make decisions supported by data related to many aspects

tutoring system to give a learner insight into the learner model as a basis to support awareness, reflection, and sense making.[25] Performance indicators on different topics are visualized and can be also adjusted by the learner (e.g. Classroom.[26] 'Tell Me More' is an application for learning the language that accompanies the results of the exercise as the basis for the visualization of the progress of students.[27] Student Activity Meter (SAM),[28] StepUp!,[29] and Student Inspector [30] have been developed to support both teachers and learners. In Slice, students' answers to questions during a face-to-face session are visualized to support reflection and group discussion.[31] In a student forum, such actions include posting, reading or replying (e.g. SNAPP,[23] Narcissus,[32] Student Success System[33]). Each activity has a timestamp and other properties such as message content, associate identity information, and category. Such information is also monitored by other systems, including the Classroom Salon, to visualize how much each student contributed and what percentage of responses have been categorized by the tags.[34] A comparative analysis of LA systems has shown that the learners prefer more detailed LA systems with elaborated analyses and personalized recommendations for their learning.[2] An overview of these educational LA applications with key features and role in a PLE is presented in Table 1, which embodies an expanded version of the Verbert *et al.* review.[11] LA systems provide descriptive information about the learning activities such as login frequency, time spent online, and accomplished results, enabling learners to monitor their achievement rates. However, further personalization and adaptive features of the LA system are desirable for improvement of current learning strategies. LA can be successful in designing Technology Enhanced Learning (TEL) systems by allowing designers to personalize courses in order to adapt them to the individual needs of learners. Many universities have established that LA can significantly improve the promotion of the institution itself in terms of allocation of resources, learner achievements, finance and administration. This paper, based on comprehensive analysis of the above-mentioned literature and our long-term experience[35–38] with implementation, use and evaluation of a personalized, recommendation-based education system, proposes a personalized LA framework that can have valuable implications on learning success prediction.

3. Personalized Learning Analytics Framework

LA uses various information about learners, and benefits for all levels of higher education stakeholders: institution, tutor/teacher and learner. Benefits can be observed in three viewpoints as follows[2]:

- **Descriptive** — analyze learning activities, understand learning habits, monitor learning progress and performances toward the goals, and compare learning sequences;
- **Actual time** — obtain real-time feedback, support automated interference, collaboration and assessments;

– **Predictive** — learning paths optimization, increase engagement, adapt to proposed recommendations and increase achievement rates.

3.1. *Learning analytics features*

LA powerful mechanisms provide numerous functionalities for different users (e.g. learners, tutors, administrators, etc.) including dashboard elements, like as visualizations of activity analyses in the Learning Management System (LMS), recommendations about further readings and adequate learning actions, self-assessment questionnaires, or additional links to related video tutorials. Features focusing on learners' behavior also include information about: time spent online, analyses and forecasts of academic performance, adaptive learning recommendations, and personalized prompts with questions about the dispositions of learners. LA mechanisms rely on analyses of various data, which can be organized as follows[2]:

– Characteristics of learner including socio-demographic data, prior knowledge, psychometric characteristics, learning strategies, academic performances and competencies.
– External data generated by using information from social media, networks or searches in the library catalog.
– Data generated by monitoring the online learning environment, including the timing and frequency of online activities and interactions (e.g. results of self-assessment, upgrade and download questionnaires and content ratings).
– Curriculum information integrated into the analysis (e.g. exam paths and expected learning outcomes).

Many dashboard applications in LA systems are designed to visualize descriptive information about past learning activities. More expanded systems include results of self-assessments.[11] Findings of a comparative study of three LA systems have shown that learners prefer more detailed LA systems with elaborated analyses and personalized recommendations for their learning.[2] Therefore, further personalization and adaptive features of the LA system are required to plan upcoming learning activities or to adapt existing learning strategies.

3.2. *Learning analytics role in a personalized learning system*

LA can be used at various educational elements, including new teaching material, appropriate syllabuses, resources, schemes of work, teaching strategies, institutional and national educational policy. There is value in being able to leverage data analytics at all these various levels.[39] LA can be used to help learners achieve success and improve withholding on the course. LA can provide a description and display of learner activities in almost real time. Faculty can suggest appropriate activities that will help them succeed.[1] For example, if learners have not read a discussion post during a certain period, this may indicate to the teacher needs to encourage them.

On the other hand, if a successful learner performs unexpectedly poorly on an assignment, the educator may engage in covering the reason why the learner was performing poorly. Another example relates to the use of data in the LMS based on which the teacher can determine if, when and how often the learner has accessed the proper LMS tools. Likewise, and consistent with the goals of the national attention on assessment, LA can help faculty to improve teaching and learning opportunities for learners[40] and potentially identify areas which are improving by monitoring learner performance and course attendance, as well as examining how this relates to grades. IBM (2001) suggested ways in which educational institutions can help in improving of learners' achievements. These include the following:

- Tracking specific learner performances.
- Classifying learner performances by particular features such as: year of study, selected subjects, nationality, etc.
- Early intervention in case of outliers' identification.
- Prediction of resources so that all learners accomplish optimum results.
- Preventing withdrawal from the courses.
- Development and application of effective teaching techniques and strategies.
- Examining standard evaluation and assessment instruments and techniques.
- Evaluating, improving and innovating curricula and syllabuses.

All these goals can mostly be achieved by collecting data from the LMS. Additionally, mining the data needed to attain these goals will greatly help to improve learner's success and optimize learning experiences May (2011) emphasized that LA has both descriptive and predictive characteristics.[41] From a descriptive perspective, LA can help us answer questions such as "What happened?", "Where was the problem?", and "What actions are needed?". LA can also help predict the answers to the following questions: "Why is this happening?", "What will happen next?", "What if these trends continue?", and "What is the best that can happen?". This approach is also in accordance with the five phases of LA use in higher education proposed by Goldstein and Katz: data extraction, performance analysis, decision support, predictive modeling and automatic response activation.[42]

Figure 1 indicates the function of LA within PLE. Individual user characteristics include demographic data, personal and social preferences, learning habits and strategies, behavior, emotions, motivation for success, proven skills and competencies, prior knowledge and academic performance, track records (e.g. course enrollment, passing course, dropouts, special needs). Social interactions include preferences for social networking tools and social networking activities.[43] Assessment, as an integral part of the learning process, can foster regulation, understanding, creation, conclusion and clarification the learning material because learners are more responsible for what they understand when they learn it, and when they show what they have understood. Assessments obtained during development provide information to learners and instructors about the learner's current performance in

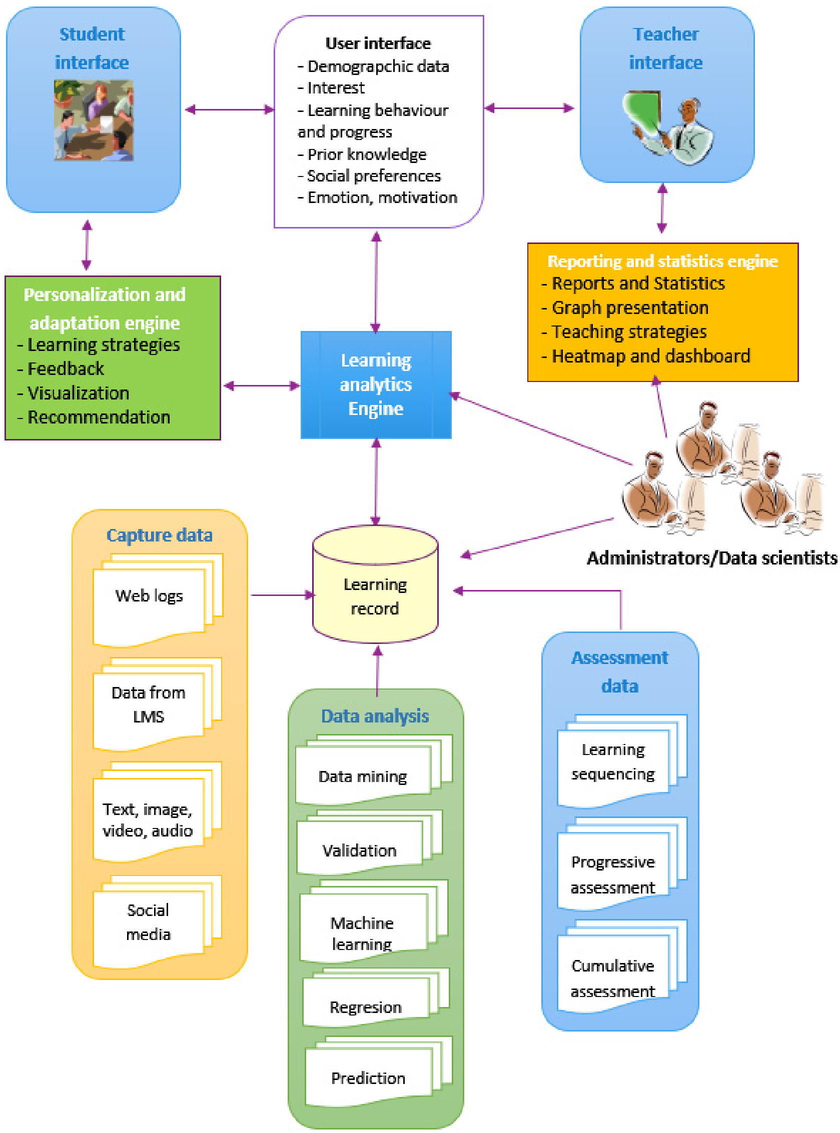

Fig. 1. Personalized learning environment.

relation to the learning objective. This is important as appropriate instructional changes can be made throughout the learning process. In a personalized learning framework, progressive assessments aim to uncover the unique qualities and deficiencies of learner to achieve and modify agreement for progress. Cumulative assessments provide information about the learners, their families, and the staff of the level of assessment authority regarding the given competencies. Most of these estimates correspond to the end of the unit or the entire course.[7,44]

3.3. *Learning analytics process*

The PLE, that we used in this study, handles different data on the learners' activities (for example login on/off, posting discussions, test results or responses to grades and surveys). In addition, context-specific and semantic information is available from the forum discussion, blog posts, Wikis, complex learning tasks and ratings of activities. The LA engine performs the data mining processes in order to validate data before further analyses are computed. These approaches include supervised and unsupervised machine learning methods as well as linear and nonlinear modeling methods. The LA engine, as the central component of the PLE is responsible for finding and then processing all these data based on separate analysis sections (Fig. 2). The capture process involved the following three phases:

(1) **Data collecting** — the process of gathering quantitative and qualitative information about variables. Good data collection requires a well-defined procedure to confirm that the data is clean, reliable and consistent.

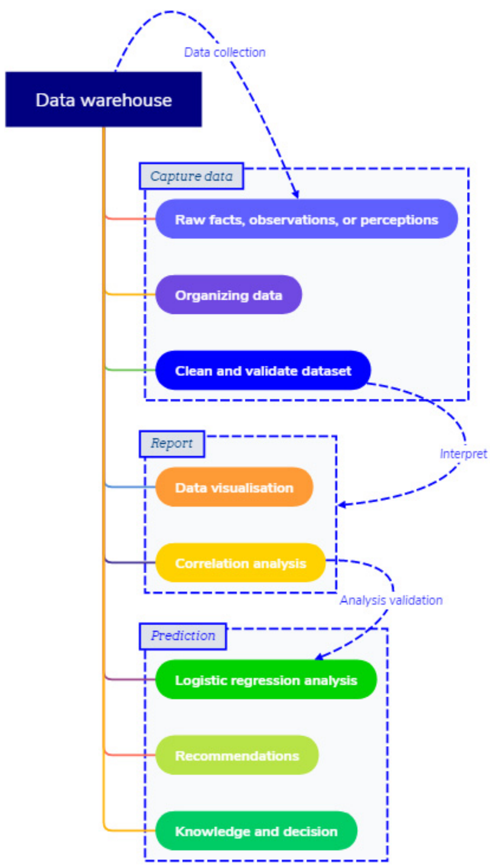

Fig. 2. Learning analytics action cycle.

(2) **Organization of data** — the technique of categorizing and organizing datasets to make them more useful.
(3) **Data cleaning and validation** — the process of identifying and adjusting (or removing) incomplete, inappropriate, inaccurate or irrelevant parts of the data and then replacing, modifying or deleting the rough data.

The phase of reporting uses to merge the data from multiple queries into a single dataset. To report on findings and conclusions drawn from the data, the analysis needs to be completed.[45] The results of a comprehensive set of analyzes are used to create a prediction model that proposes suggestions for further learning strategies. In LA, there is a process of collecting and managing data to provide learners with the data they need to gain knowledge, helping them to improve their course experience.

4. Learner Success Prediction — Case Study

The purpose of our experimental study was to validate the student profile of the proposed LA framework based on data obtained from Educational software course in Moodle LMS. Correlations were used to identify trends for the trainees based on multiple background and demographics, academic and course-related factors. In order to identify predictive models for learner success, which is the most important part of the Learning Analytics Process (Fig. 2), logistic regression tests have been performed. Data analysis for this study was completed to answer the following research question: Which predictors are important for learner characteristics that lead to the successful completion of the coursework? This section reports the results of the quantitative data analysis. Section 4 describes the details of the various statistical tests completed as part of this study. The research question will be addressed within the discussion and conclusions of the study.

4.1. *Data models*

For our experimental study, population was determined based on the enrollment choices made by learners. It included all learners who were actively enrolled in the Educational software course that was offered during the Summer semesters of three school years (2016/2017, 2017/2018, 2018/2019), at the Faculty of Sciences, University of Novi Sad.

Most of the learners were from the grammar schools followed from economic and technical schools, and the rest of the respondents were classified into a vocational school. A grammar school is an academically oriented secondary school, which prepares learners for higher education at a university. A grammar school education takes four years following a compulsory eight-year elementary education and ending with a final aptitude test called "Matura". The final test is standardized at the state level and can serve as an entrance qualification for universities. The subjects taught are the mother tongue, mathematics, one to three foreign languages, history, geography, informatics (computer science), the natural sciences (biology, chemistry, physics), history of art, music, philosophy, logic, physical education and the social sciences (sociology, ethics or religious education, psychology, politics and economy). Religious subject is optional.

Professional/vocational schools specialize learners in a particular field and awards them with a first professional degree. It takes three or four years to complete. Some examples of such schools are Economy School, Medical School, Chemistry School, Technical School, Graphics School, etc. Usually, they teach 10–14 general subjects (Serbian, mathematics, geography, biology, history, foreign language, etc.), a few professional subjects that are different for almost every course (hygiene in a nurse-technician course at medical schools, for example) and a compulsory block of practice classes.

With regard to post-secondary education, vocational schools are traditionally distinguished from grammar school by their focus on job-specific training to learners who are typically bound for one of the skilled trades, rather than providing academic training for learners pursuing careers in a professional discipline. Economic school introduce economics as a key strand of History, Government, and Social Studies, and to develop a critical understanding of the assumptions underpinning economics. Economics is a unique way of thinking that offers insights into human behavior in a world of different values, resources and cultures. Learners who think in an economic way will understand concepts better and how each concept relates to the others. High School of Economics, within the scope of its activities, includes economic and law courses, which belong to the field of economics, law and administration. These courses provide learners with opportunities to learn about the challenges and issues in a contemporary economic context. Learners develop their analytical, problem solving and communication skills to make informed judgements about economic issues.

Technical schools refer to secondary education designed to provide technical skills required to complete the tasks of a particular and specific job. They use innovative, leading-edge technology and discovery to give secondary school learners the skills they need to flourish in the global economy. They are a link between schools and industry to provide innovative learning programs. Technical Schools challenge learners to solve real-world problems and prepare them for the future world of work. Some of them are preparing for producing goods that they can sell from their own premises (e.g. bootmakers, bakers, carpenters, glassmakers, potters, stonecutters, coppersmiths, jewellers, engraver); others (e.g. machining operator, drive technician, bookbinders, mechanical technician) were employed to do one part of the production that required a variety of skilled workers.

Participants/Sample. The sample consisted of $N = 174$ learners (69 females; 105 males). Since the subject is elective from the first to the fourth year of study, there is a difference in age. The age of the learners in the study population were categorized into four groups. The percentage of learners in each group is shown in Fig. 3.

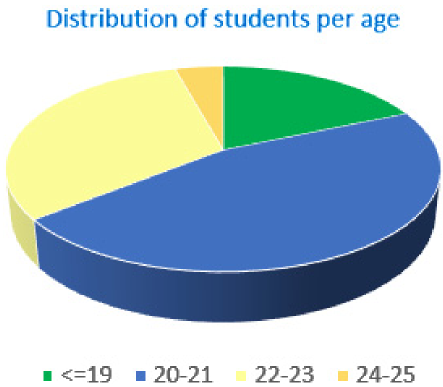

Fig. 3. Distribution of learners per age.

Previous education. We have collected data about previously finished high schools of the learners in the study population ($N = 174$) and compared them with data obtained for the first-year learners ($N = 444$). The majority of the first-year learners finished grammar schools (64%), economic schools (16%), technical school (11%) and vocational schools (9%).

Table 2 displays the distribution of the set of known characteristics of the first-year learners by gender, previous education, and age. There is a significantly higher percentage of females that are first-year learners as compared to the population used in this study. Additionally, the distribution of age in the study population shifts from the first-year learner, because the course we have chosen is the elective course from the first to the fourth year.

Table 2. Learners demographics.

	First-year population		Population in the study	
	$N(447)$	Population %	$N(174)$	Population %
Gender				
Female	294	65.77	69	39.65
Male	153	34.23	105	60.34
Age				
<= 19	330	73.83	39	22.42
20–21	63	14.09	96	37.93
22–23	36	8.05	66	34.48
24–25	18	4.03	9	5.17
Previous education				
Grammar school	285	63.76	69	39.65
Economic school	75	16.78	48	27.59
Technical school	48	10.74	36	20.69
Vocational school	39	8.72	21	12.07

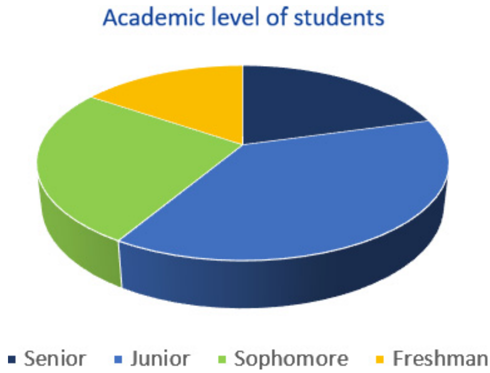

Fig. 4. Academic level of learners.

Academic Level of Learners. The learners enrolled in the course Educational software ranged from sophomore to senior learners. The distribution of the academic level of learners enrolled in the classes can be seen in Fig. 4.

4.2. *Predictors of academic success*

The results of the analysis, we used to create several prediction models, will be presented in the rest of this section. We used a set of correlational tests to identify which academic and demographic factors were most closely associated with learner success. The correlation tests were followed by a series of logistic regression analyses. These results were used to create figures and tables for the predict phases of the LA process. The model emphasizes the prospect of learners. Several common success factors were identified in this study: gender, age, academic level, the term of enrollment and previous education. This finding indicates that these characteristics are predictive of stronger academic performance despite the course format. The overall average final grade for the course was 8.017 (out of 10) with 65.517% of the learners receiving a grade 8 or better. Nearly 17% of learners enrolled in the course finished it earning a grade 10, while 8.89% earned grade 5 (not passed exam) or withdrew from the course. Of those learners who received failing grades, approximately 30% opted to withdraw from the class after the add/drop deadline. This study identified a relationship between academic level, or the amount of time a learner had been attending college, and final grade. For the study population, the higher the academic level, the higher the final grade average for enrollments, which was in alignment with the literature.[46,47]

A series of four different logistic regression models are created in the process of identifying the best model for predicting success. Separate logistic regression models were created for demographic variables, academic variables and previous education to identify if one of these areas had a larger influence than the others before creating a full model using all the variables.

Model 1 — based on demographic variables. The first model was limited to demographic variables. For this model, the Nagelkerke R^2 estimate reflects the variability of success that can be attributed to the variables included in the logistic regression model. The combination of demographic variables used in the model accounts for two influences on the likelihood of success ($R^2 = 0.0482$). Because the model explains such a low percentage of the likelihood of success, it was only an accurate predictor 55.16% of the time, based on the area under the curve (ROC Curve Model).

Model 2 — based on academic variables on success in courses. A separate model was created to evaluate the effect of academic variables on success in courses. The Nagelkerke R^2 estimate showed that academic variables accounted for 42.16% of the likelihood of success across the study population, and the area under the curve indicated the model was accurate in predicting success 79.44% of the time.

Model 3 — based on previous education. This model evaluated variables associated to the previous education. The Nagelkerke's R^2 estimation showed that variables related to the previous education influenced 5.13% of the likelihood of success. When variables related to the previous education were used as a prediction model for the study population the area under the curve showed the model was accurate in predicting success 63.18% of the time.

Full Prediction Model. While each of the described models addresses some features of the predictors of success for learners, the full model includes complete view based on all analyzed variables. Table 3 shows the relative level of predictability for each set of variables, but the full model was found to be the most significant predictor. For the study population the test of the full model was statistically significant, X^2 $(46, N = 174) = 41.104, p < 0.0001$. The estimated Nagelkerke R^2 indicates the combination of variables used in the final model account for a 44.22% influence on the likelihood of success. This model properly predicts success for 88.15% of the learners in the study population, according to the ROC Curve Model, with a specificity of 44.8% and sensitivity of 95.1%.

4.3. *Results of analysis*

Data analysis for this study was performed to identify relationships between the variables of the learning profiles and the model of success prediction. The purpose

Table 3. Summary of logistic regression for three models.

Variables	Model 1	Model 2	Model 3
Significance	$p < 0.0001$	$p < 0.0001$	$p < 0.0001$
Degrees of freedom	10	19	15
Nagelkerke's pseudo R^2	0.0482	0.4216	0.0513
Area under ROC curve	0.5516	0.7944	0.6318

of this study was to determine which demographic, academic and educational characteristics are closely related to successfully completed courses. The results of the analysis will be discussed in this section. As well, a comparison of the literature considerations and findings from the data collected at our institution for this study will be given. Several common success factors were identified in this study: gender, age, academic level and previous education. When considering demographic characteristics, females performed better than male learners in course enrollments. This finding are similar with the studies completed by.[48,49] Age was challenging to use as a predictive behavior because both older and younger learners earned higher average grades than middle-aged learners. Studies reviewed in the literature had mixed results based on the use of age as a predictor, so these results coincide with the previous studies. Several studies found younger learners were more likely to be successful in their course enrollments,[48,49] while other studies found older learners were more likely to be successful.[46,50] The younger learner success is likely due to the number of learners enrolled in concurrent enrollment courses while the older learners often have found that first-year learners earned lower grades than their counterparts who are not first-year learners. This study found that first-year learners earned lower grades than their counterparts. First-year learners tend to have lower levels of college readiness as compared to learners at senior years of study.[51]

This study identified a relationship between academic level, or the amount of time a learner had been attending college, and final grade. For the study population, the higher the academic level, the higher the final grade average for enrollments, which was in accordance to the literature.[46,47] Other studies that addressed the relationship between academic level and final grade reported that sophomores outperformed juniors, but both significantly outperformed freshmen.[46,47] One explanation for this finding is the high number of concurrently enrolled learners. One more academic factor of interest was to consider a learner's average grade point and previous education. There was a very weak correlation between average grade point from high school and final grade in a course ($r = 0.1302$, $p < 0.0001$). This result aligns with the literature. While, there are studies stated that the high school average grade point is one of the greatest predictors of graduation at college.[52] There are studies which also reported about connection between high school average grade point and success at the university level.[53] They reported that many learners who did not begin their higher education directly after high school change the level of motivation and achieve a worse success. We also analyzed the success of learners based on their previous education and concluded that the best results are achieved by learners who came from grammar school, then from economical schools and finally from technical school. In the literature, we can find classification of learners based on previous education which would allow the administrative and academic staff to identify learners who would be "at risk" of dropping the course even before they start with their study. Then the learner support systems, such as orientation, advising, and mentoring programs, could be used to motivate, encourage and positively impact the academic successes of such learners.

5. Conclusions

Personalized learning models support the learning process of learners by encouraging them to actively participate in the compact learning environment, becoming aware of their specific adaptation needs, recognizing and applying the learning methodologies that are most appropriate for them. Personalized learning has shown that there are no two learners who are learning similarly or at a similar pace. With personalized learning, important capabilities and different skills can be enhanced, for example, critical thinking, correspondence, collaborative effort, communication and computerized knowledge, individual and social commitment, advancement, imagination and knowledge around the world. Advanced PLEs provide learning features that trainees can use in independent learning. Involved in learning environments the LA engine can encourage information achievement, ability advancement and utilization of learning in different tasks. The model proposed for personalized enhanced learning, teaching and self-directed expertise implies that the learning process is centered on the demands, qualities and longing of each individual learner. Learners take a dynamic part in planning their way of training and developing responsibilities for their own learning achievements.

The purpose of our experimental study presented in this paper was to validate the learner profile performed by applying LA to data obtained from student's enrollment and data obtained from LMS, which includes learning performances such as the total amount of clicks, the number of online sessions, the total time online, and the total amount of views. Correlations have been used to identify trends of learning performances based on demographic data, academic and previous education related factors. In order to identify predictive models for learner's success logistic regression tests have been performed.

The results of this study could be enhanced with examination arranged around learner observations, which can be used as a model for other courses. Analysis of data on learners' attendance and withdrawing from courses could be expanded with information gained from these learners as to why they chose to withdraw. Recognizing which learners choose to attend the same university after graduation, or could benefit from information on how many learners that started as a high school learner graduate college along with information how long it takes them to complete their degrees.

We hope that research results presented in this paper and the implications derived from them will advance the discussion about building effective personalized learning system based on LA techniques. Our findings can be used as the basis for generating feedback and recommendations to the educational stakeholders when preparing marketing and recruitment strategies and policies for attracting new learners. Teachers, learners, researchers and LMS designers are potential stakeholders who can benefit from the knowledge discovered through LA process and EDM to improve and facilitate the learners' process.

Acknowledgement

The authors acknowledge financial support of the Ministry of Education, Science and Technological Development of the Republic of Serbia (Grant No. 451-03-68/2020-14/200125).

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